CVDMagic: A Mobile Based Study for CVD Risk Detection in Rural India

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ABSTRACT

Cardio-Vascular Diseases (CVD) are one of the major healthcare problems across the world, causing deaths for nearly 17 million people every year. With more than 80% of all CVD cases occurring in developing countries, it is a big challenge that needs immediate attention. Specifically for India, World Health Organization (WHO) and many other organizations have predicted rapid growth of CVD patients in near future. It is known that CVD can be prevented or deferred, if detected in its earlier stages and by subsequently adapting to appropriate preventive methods. Cost and availability of lab equipments - for early diagnosis of CVD - act as deterrents in controlling the spread of CVD cases in India, particularly in the rural parts.

Non-laboratory based methods overcome the factor of cost while mobile technology provides the availability to allow for approaches that can detect CVD risk early even in the remotest part of the country. In this paper we present *CVDMagic* - a mobile phone based study for CVD risk detection. Our study, a mixed-method approach, uses two non-laboratory based approaches (including one proposed by WHO) together with inputs from local doctors corresponding to Indian context. We also present analysis from initial survey (of 169 people) from a pilot deployment of *CVDMagic* . The preliminary analysis suggests that mobile-based approaches can be used for efficiently collecting required data leading to accurate, low-cost, non-laboratory based early detection of CVD risk in Indian context.

Categories and Subject Descriptors

J.3 [**LIFE AND MEDICAL SCIENCES**]: Medical information systems

General Terms

Design, Experimentation, Measurement

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Keywords

Healthcare, Cardio Vascular Disease, Mobile Health

1. INTRODUCTION

With its population growth and lack of resources, India is particularly vulnerable to CVD related diseases. Various healthcare organizations estimate that if appropriate measures are not taken, CVD will become the largest killer disease in India by 2020 [6]. An estimate by World Health Organization (WHO) calculates a loss of nearly 230 billion dollars in national income for India due to premature deaths by heart disease, stroke and diabetes[1]. Recent changes in lifestyle are reasons for the increase in CVD cases in India. A worrying fact is that CVD is also emerging in rural areas that have traditionally been free from such diseases [9, 16]. Despite a growth in overall healthcare resources and manpower in India, there is still a considerable lack of resources in Indian rural settings e.g. ratio of hospital beds to population in rural areas is fifteen times lower than that for urban areas and ratio of doctors to rural population is also almost six times lower compared to urban population.

A good strategy in such constrained environments is to develop effective non-laboratory based approaches for early detection to complement existing infrastructure and thus allowing preventive measures to be adopted. The new approaches must be able to work in resource constrained environment, prevalent in rural Indian settings.

Advances in mobile technology has led to the development of mobile phone based solutions for efficient delivery of healthcare services. Ever lowering cost of mobile phones and their popularity makes them ideal platform for developing solutions for early detection of CVD. Already several mobile based solutions have been used in the healthcare domain for a diverse set of activities such as 1) Disease surveillance and tracking, 2) Remote data collection and patient monitoring, 3) Education and awareness and 4)Healthcare worker training. Several of these studies have reported increased accuracy [2, 3], reduced cost [3, 13] and improved efficiency [3, 4, 7] in healthcare data collection using mobile phone compared to paper based approach. Such studies further motivate exploring opportunities for building mobile based applications for early detection of CVD.

In this paper we are presenting *CVDMagic*, a mobile phone based framework that encodes multiple non-laboratory approaches for CVD risk detection. *CVDMagic* is based upon

[1] `http://www.who.int/chp/chronic_disease_report/full_report.pdf`

open source Sana framework[2] developed at MIT. With a mobile phone front-end to rural healthcare workers and back-end server (at a central location), we can achieve early diagnosis as well as make people aware of their CVD risk status in a cost-effective way with minimal resources. We also present results from a field deployment in rural areas of Bhatinda district in Punjab, India. The preliminary analysis of results indicates that non-laboratory based approaches (derived from clinical data from western population) show contradictory results for Indian population, making it necessary to develop approaches specifically for Indian population, as also suggested by Kanjilal et al.[10].

To summarize, primary contributions of this paper are:

1. Mobile based study encoding previously proposed non-laboratory approaches for CVD risk detection together with feedback from doctors local to our case study environment

2. Analysis on a pilot of our system, conducted with 169 people, demonstrating the need for risk estimation specific to Indian population

Next, in Section 2, we discuss related work in non-laboratory based CVD risk detection and using mobile phones for healthcare applications. In Section 3, we explain the complete system in detail. We present detailed analysis of the data collected from our pilot study in Section 4. Finally, we conclude and present future directions in Section 5.

2. RELATED WORK

Non-laboratory based early detection of CVD risk has been an area of study [1, 5] because of its non-requirement of costly lab equipments. Gaziano et al. [5] demonstrated an accuracy comparable to laboratory based approaches on clinical data from U.S population. World Health Organization (WHO) has proposed "WHO CVD-Risk Management Package" [1] to assess CVD risk feasibility in low and medium resource settings. Both of these approaches [1, 5] differ in their CVD risk calculation method and to the best of our knowledge, no previous results exist that show applicability of any of the approaches for Indian population.

Technological solutions have been used in healthcare for community awareness [12]. Mohan et al. [12] used community awareness programs for motivating people to adopt healthy lifestyle thereby preventing non-communicable disease. Our *CVDMagic* system can support their approach (e.g. to send awareness videos on mobile phones of patients or for collecting patient responses using forms on mobile phones) and make it more scalable. Vale et al. [17] proposed a system for improving coronary health of patients. They used telephonic interventions and a software platform to train people for improving their coronary health conditions. In their system patients were trained for 6 months, creating their own health plans during this duration. These health plans were then shared with their coach (physician). Later coach could intervene using telephone to suggest modifications or to check their adherence to plan. Results indicated that these telephonic interventions were useful and helped people in improving their health conditions. Such additional activities, for increased awareness, can complement our *CVDMagic* system.

[2]http://sanamobile.org/

Mobile phones have also been used for intervention in healthcare applications in several studies. HeatToGo [8] is one such application designed for CVD patients. In this study, Jin et al. proposed a mobile phone based personalized medicine technology, for CVD, capable of performing continuous monitoring and recording of ECG in real time, automatically detecting and classifying different CVD conditions and generating individualized cardiac health summary in common language. However, their application requires high-end phones with expensive interface to ECG sensor while we aim to develop an approach that does not have such requirements. Microsoft with its partner companies has designed MediNet[3] which is a health management system designed to give timely telephonic intervention to diabetic and CVD patients. Focus of the system is to help patient in improving self-care using telephonic intervention. We do not know of any deployment of this system for proven effectiveness in the field.

Another use of mobile phones was demonstrated by Ramachandran et al. [14]. They worked to identify methods that work best to improve communication between healthcare worker and patient. It was found that rural healthcare workers in India, due to lack of good training, motivation and credibility, are not able to effectively convince patients to adopt healthy practices. In their study, they found that phone-based dialogue messages significantly improve the quality of counselling sessions and increase discussion between healthcare workers and clients (although they did not provide any statistical results).

The primary purpose of most of previously proposed non-laboratory based CVD risk detection approaches has been to design a set of parameters that influence accurate diagnosis of CVD risk using traditional way of data collection. On the other hand, *CVDMagic* provides a complete end-to-end solution from data collection to automated risk detection.

3. SYSTEM DESIGN

We have developed our *CVDMagic* system using the open source Sana mHealth application framework. Sana framework consists of three tier architecture - Android based mobile client, central server (hosting openMRS, an open source medical record system) and a middle layer, MDS (Mobile Dispatch Server) connecting the mobile client and the server. Sana mobile client allows the flexibility of creating mobile based forms that can be used to collect patient data. Collected data is buffered locally on the phone and uploaded opportunistically, using GPRS, to the central server for further analysis, based on available cellular connectivity. Sana, with its opportunistic upload feature, fits nicely in resource-constrained environments like rural India where connectivity is often intermittent. Additionally, Sana (core of *CVDMagic* system) can increase or decrease the data packet size based on high or low signal strength respectively, thus uploading data in an energy efficient manner. Building *CVDMagic* on an existing framework allowed for rapid development for us, with a robust platform underneath, and we also contributed in extending Sana with our work.

Though Sana is primarily for Android phones which are usually high-end, we also developed a Symbian-based client to allow use of Sana on low-end phones. Since Symbian is the

[3]http://www.mobiquitous.org/2009/docs/wip_MediNet-Sultan.pdf

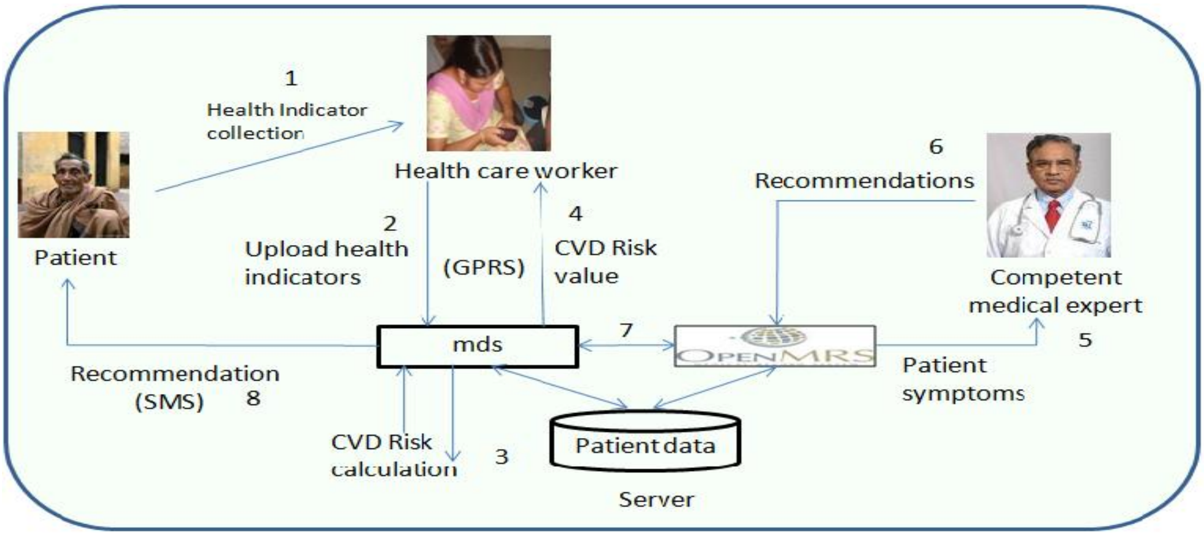


Figure 1: *CVDMagic* workflow

most popular platform in India, this helped us in reducing cost further as well as allow heterogeneous devices to be used.

Complete workflow of our *CVDMagic* system is shown in Fig. 1. We train healthcare workers on using the mobile application of *CVDMagic* system. The healthcare worker goes door-to-door to collect information about health indicators sought in our mobile application (as step 1 in Fig. 1). Please note that only healthcare worker needs to have phone and not the people being examined. This helps in keeping costs low and also having a human face while providing them with more information on CVD risks helps in creating awareness and also receives greater attention from the target population. Information, thus, collected is uploaded to a central server using GPRS (steps 2 and 7 in Fig. 1).

At the server we are using rule based approaches to calculate CVD risks. Among previous work, we have decided to use approach suggested by Gaziano et al. [5] and recommendations of WHO (we are using the second approach) [1]. However since there was no study of their work on Indian population, so to account for parameters specific to local population, we have consulted local doctors and encoded the non overlapping parameters (with the other two non-laboratory based approaches) in our application as well which works as a third approach to calculate CVD risk in our system. The approach of local doctors was limited to asking only two questions:

1. Did you ever have feeling of breathlessness?
2. Did you ever have problem in climbing stairs?

A *yes* answer to any of the question was considered a high risk. The approaches of Gaziano et al. [5] and WHO [1] provide a flowchart which takes values with respect to specific parameters, e.g., for BMI, BP, smoking status etc. that are taken on mobile phone. In total around 15 questions were asked per participant and measurements for height, weight, diabetic status and blood pressures were taken. Each question was a separate screen-shot on the mobile phone and had basic checks for invalid values to avoid accidental errors in input. Besides, certain questions were made mandatory without which, the software did not allow to proceed, this was helpful in ensuring that all the necessary field were filled which is not possible on a paper-based form. Since the healthcare worker had to input only one value per screen, it was very easy for them to use a smart-phone for this purpose. The local doctors's approach was only perception-based, which may be a reason for less overlap with other approaches.

The server calculates CVD risks (step 3 in Fig. 1) and sends it back to the mobile phone of the healthcare worker (step 4 in Fig. 1) from where the data on health indicators was earlier collected. The calculation of CVD risk itself is a simple task that can be performed on the mobile phone, however, collecting data about health indicators at a central location (using openMRS) has its own advantages in maintaining patient history, so we also offloaded the task of CVD risk detection to the central server as well. This also allows our *CVDMagic* system to send the CVD risk directly to the patients provided their mobile phone numbers were also collected with other health indicators (step 8 in Fig. 1). The notification is a simple sms message thus any phone with the patient can receive it. This feature can allow our *CVDMagic* system to send other notifications (e.g. to create awareness about other diseases or activities to promote better health etc.) to patients directly. However, if a healthcare worker wishes, the result can be calculated on the phone which the healthcare worker can deliver immediately and face-to-face. This feature can be useful in cases of remote regions where there may not be a connection available with server. Also the sms notification is a feature that our system has, for our current study, the healthcare workers themselves delivered the results.

A medical expert can also log into central server (hosting openMRS) remotely, look at the queue of pending patients and put in comments that may include diagnosis corresponding to the given information or may seek additional information about the patient (step 5 and 6 in Fig. 1). These comments are then pushed back to the mobile phone of healthcare worker (or the patient) using sms (step 7 in Fig. 1).

Our design choices for *CVDMagic* system give us some unique advantages:

1. Being a mobile based solution, we can easily encode

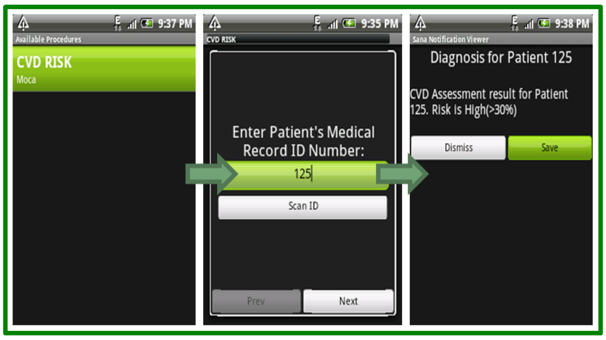


Figure 2: A few steps in the mobile form of *CVDMagic*

simple rule based approaches to partially automate some of the decision making processes removing the necessary human and physical infrastructure required otherwise. The remote diagnosis feature with OpenMRS server removes the requirement of the physical presence of a doctor.

2. From the perspective of healthcare worker, *CVDMagic* system results in increased accuracy and efficiency:
   (a) Automated CVD risk calculation consumes less time compared to healthcare worker calculating the CVD risk on her own in a paper-based approach.
   (b) For activities such as patient registration, record keeping etc., *CVDMagic* system allows data collection through customizable forms in the mobile client (please refer to Fig. 2). Automated uploading of the data to the server further saves manual effort of entering it from paper based form to a server. Also, in-built logic in *CVDMagic* system (e.g. check for valid values for an entry) reduces the manual error of incorrect data type insertion. Since images of patient/disease-region can also be stored, the data thus becomes more complete compared to paper based forms.
   (c) The mobile phone itself can calculate CVD risk if so desired. This feature can be used when there is no connectivity or if the health worker wishes to deliver the risk immediately and face-to-face.

4. OBSERVATIONS AND ANALYSIS

We did a pilot of our *CVDMagic* system in collaboration with Electronic Health Point (EHP)[4], India. The mission of EHP is to transform rural healthcare and improve wellness, productivity and quality of life. EHP clinics are governed by Health Point Service India (HSI), that provides safe drinking water, medicine, comprehensive diagnostic tools and tele-medicine based health care services to rural population. EHP has its clinics set up in rural areas of Doda, Kot Bhai, Mallan, Gurusar, Hari Ke Kalan, Pakhi Kalan, and Golewala in Bhatinda district of the state of Punjab, India. We selected the same neighborhood for field trial of *CVDMagic* .

We trained two primary healthcare workers, employed with EHP, to conduct door-to-door data collection in the neighbourhood. Phones for the study were provided by us, but no financial incentives were given to the healthcare workers to use phones. The healthcare workers had done a general nursing diploma course of 3 years after their secondary education (equivalent to baccalaureate) and had basic knowledge of English as required by *CVDMagic* . Healthcare worker were also trained to do spot measurements for blood pressure, diabetes, weight, and height as they are required for accurate detection of CVD risk as per the encoded approaches. They also demonstrated their ability in performing our tasks before starting the study. In our training of healthcare workers with *CVDMagic* , they were able to pick up the complete process very quickly with little training despite the fact that she has never used smart phone before. There may be several reasons for this, including personal drive, an opportunity to use a smart phone (provided by us for the field study) and excitement of using a new technology among others.

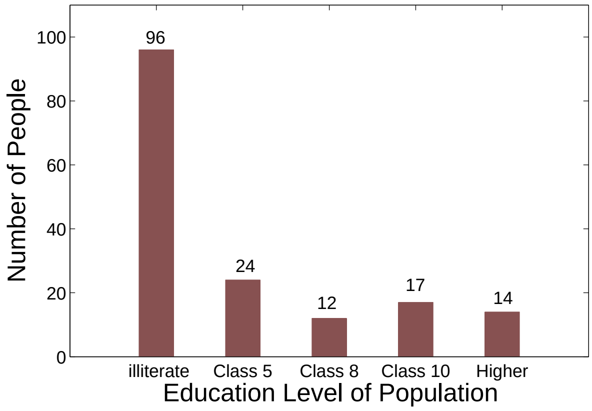


Figure 3: Education level of surveyed population

We collected data from 169 people belonging to age group 32-95, of which 52 were male and 117 were female. With healthcare workers themselves being female, they were more comfortable in discussions with females, resulting in higher bias towards female population in our study. We also preferred to interview more of middle and old age people since they are them more prone to CVD risk. Except the above two factors, no other bias was present in selecting a specific category of people. We were not in a remote region and did not have connectivity problem, so the store-and-forward feature of *CVDMagic* was not used.

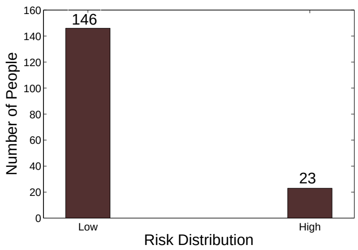
Table 1 gives some important parameters of our target population that we collected. In Fig. 3, we can see in detail the education level of the population that was surveyed in this study. More than 56% (96 people out of 169) are illiterate. Further, 39.05% people were found to be unaware of their diabetic status. Given that Punjab has above average literacy rate of India, we found our target set a good representation of population in rural Indian context in terms of literacy and awareness. Above observation led us to conclude that the primary requirement for any healthcare application designed for rural Indian context is to account for low education level as well as lack of awareness about health parameters amongst the target population.

Fig. 4 shows risk distribution of population based on approaches proposed by Gaziano et al. [5] and local doctors. Since local doctors only suggested parameters indicative of

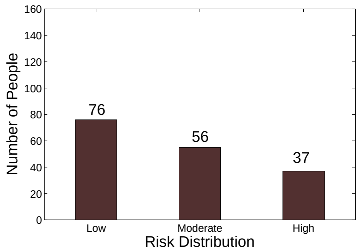
[4]http://www.ehealthpoint.com/

Table 1: Target Population Profile

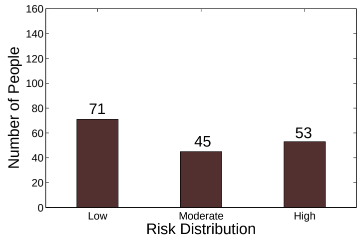
	Men (52)	Women (117)	All (169)
Mean age	52.5	50	50
Mean Diastolic Blood Pressure (mmHg)	90	80	90
Mean Systolic Blood Pressure (mmHg)	140	140	140
Mean Glucometer Reading	99	106	105
Smoker (%)	11.53	0	3.55
Alcohol consumption (%)	30.76	0	9.46
Literate (%)	48.07	41.02	43.19
Mean BMI	25.31	25.96	25.78



(a) Based on parameters from local doctors



(b) Based on parameters suggested by TA Gaziano et. al. [5]



(c) Based on combination of local doctors and [5]

Figure 4: CVD Risk distribution of the surveyed population based on parameters suggested in different encoded approaches in *CVDMagic* system

high CVD risk, hence there is no categorization of moderate risk to CVD. In the combined plot, Fig. 4c, a person is diagnosed as high risk to CVD if any one of the two approaches diagnose him as high risk, moderate if [5] diagnose him as moderate while local doctors diagnose him as low risk and low if both the approaches diagnose him as low risk to CVD. People who were diagnosed with moderate or high CVD risk were given information on potential risks associated with CVD and were encouraged to visit the local EHP clinic for detailed clinical tests. Around 58% (98 people) of the population were found to be having high or moderate risk for CVD in our study. We did not use results of WHO approach to categorize people for CVD risk category as we do not find any published result demonstrating the accuracy of this test. Though the same is true for local doctors, but we believe that a local doctor should be taken into account for their knowledge and experience of the context.

We observed that the three approaches were also giving contradictory results. To analyse it more closely, we combined all the three approaches ([1, 5] and from local doctors) and calculated the CVD risk of population. Here a person is considered as having high or moderate risk to CVD if there is at least one approach that detects high or moderate risk respectively. The person is considered low risk to CVD if all the three approaches detect low risk to CVD. Comparing the combined risk distribution in Fig. 5 with that in Fig. 4c (calculated only based on [5] and local doctors), we see that the number of moderate or high risk category people increase from 58% (98) to 68.6% (116). Further there is a stark difference in the number of people diagnosed with high or low CVD risk by different approaches: Approach suggested by local doctors categorized 23 and 146 people for high and low CVD risk respectively (Fig. 4a); Approach from WHO [1] categorized 50 and 119 people for high and low CVD risk respectively; Approach proposed by Gaziano et al. [5] categorized 37 and 76 people in high and low CVD risk category respectively. Fig. 6 further illustrates this difference wherein we can observe that out of 169 cases, all the three approaches agree with each other in only 69 (40.82%) cases (category 1 in Fig. 6). When compared in pairs, there are 24 (14.2%) cases wherein approaches as suggested by our local doctors and as suggested by TA. Gaziano et al. [5] match while approach from WHO conflicts (category 2 in Fig. 6), 14 (8.28%) cases wherein approaches suggested by TA. Gaziano et al. [5] and WHO match while the one suggested by local doctors conflicts (category 3 in Fig. 6) and 61 (36.09%) cases wherein approaches from the local doctors and WHO match while the one proposed by TA Gaziano et al. [5] conflicts (category 4 in Fig. 6). Another interesting aspect of this analysis is that two of the published risk detection approaches, i.e. TA. Gaziano et al. [5] and WHO [1] risk detection method conflict in 84 (49.70%) cases (category 5 in Fig. 6).

These figures clearly indicate the difference in results when using different approaches, thus supporting observation by other researchers [10, 15] who also advocate more studies to identify a robust technique (set of parameters) for non-laboratory based CVD risk detection for Indian population. While [10, 15] used data collected by previous studies for CVD risk assessment, we conducted door-to-door surveys to collect data from rural Indians; moreover, the data of Kanjilal et al. [10] is from hospitals in metro cities which are usually beyond the reach of common rural people in India due to economic and work constraints. Their approaches [10, 15] used parameters which required a thorough laboratory examination (e.g. HDL or LDL etc.), while in our approach spot measurements were enough to provide required parameters for CVD risk assessment. Because of such less requirements of our approach, we feel that in a resource constrained environment our approach is more suitable for a mass-level

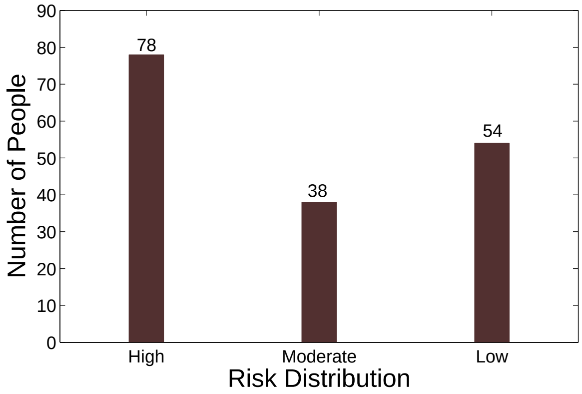


Figure 5: CVD risk distribution as per *combination approach*

CVD risk assessment study.

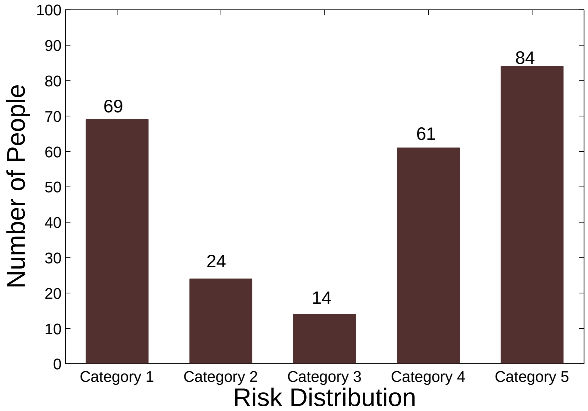


Figure 6: CVD risk distribution by different combination of encoded approaches

Prior studies have shown a gender bias in CVD risk with men being more prone to the disease than women [11]. Fig. 7 shows the corresponding gender based CVD risk from our pilot study. 52.99% of the women surveyed and 71.15% of the men surveyed were found to be high or moderate risk to CVD confirming prior published results.

Another alarming statistic emerging from this study is that 22% of the people below the age of 50 (considered as an early age) were found to be high or moderate risk for CVD. Some of the recent studies have also demonstrated that in India, the average age of first heart attack is 53, which is 6 years below the average from the rest of the world. From our data, Table 2 indicates that youngest person to have High CVD risk is of 40, and in Table 3, we can clearly see that after the age of sixty risk of being diagnosed with moderate/high risk increases to 97% from 43%. A consistent parameter that strongly correlates with moderate/high to CVD is diabetic level. In our data, 28 out of 29 people having glucose level higher than 140 mg/dl were diagnosed with moderate/high risk.

After the study was done, we also interviewed the healthcare worker and asked for her experience in using our system. She found our system very easy to use as compared to paper-based approaches. She specifically liked the feature of

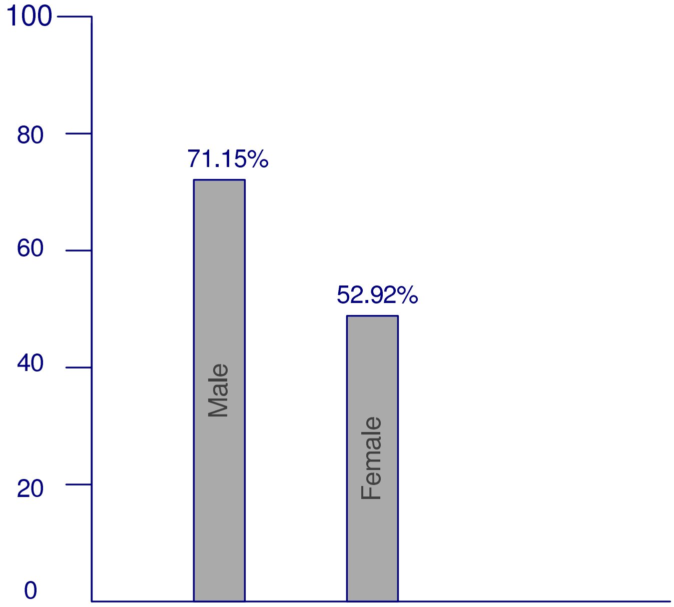


Figure 7: Gender based CVD risk distribution

automated risk calculation just after collecting the data and reported that she would prefer a mobile-based solution over paper-based for any future health-related study. On asking about improvements to our system, she said that phone-based client was sufficiently good, to conduct such studies and she was completely satisfied with its use. Our concern regarding poor education level of the target population was also validated. The healthcare worker reported that despite being told of high/moderate risk, most of the people took it lightly. She emphasized the need to have more such studies, at a larger scale, and to educate people about CVD risks and make them aware that preventive measures can defer CVD. Our *CVDMagic* system makes both of these tasks easy and is highly scalable.

We also interviewed IT administrator at EHP whose regular duties include IT infrastructure plan, implementation, maintenance, and managing IT Services Support. We wanted his experience on using *CVDMagic* from IT perspective. He mentioned that in previous works he has felt collection and collation of data to be most time-consuming task as they required manual entry to the system - this corroborated experience of the healthcare worker in collecting data from the patients. He liked *CVDMagic* for its ease of use and himself explored around various server-side feature of *CVDMagic* . He mentioned to have seen other IT systems at other healthcare places and he found *CVDMagic* much easier compared to other system that he has experienced.

5. CONCLUSIONS AND FUTURE WORK

Increasing risk of CVD and lack of appropriate resources necessitate developing a robust non-laboratory based CVD risk detection approach for Indian population. In this work, we proposed a mobile phone based system -*CVDMagic* - that can encode proposed non-laboratory based CVD risk diagnosis methods and give indication of CVD risk status. For this work we used previously proposed approaches [5, 1] as well as a third approach after consultation with local doctors. Proposed *CVDMagic* system is built within open

Table 2: Age extremes in CVD risk

	Low	Moderate/High
Youngest	32	40
Oldest	60	95

Table 3: CVD risk with ageing

	Before 60 (124)	Above 60 (45)
Low	70 (56.45%)	1 (2.22%)
Moderate	31 (25%)	14 (31.11%)
High	23 (18.54%)	30 (66.66%)

source Sana framework that allows for local data buffering and bandwidth management thus making it suitable for intermittent connectivity regions like India.

The *CVDMagic* also gives option of uploading the medical cases to a central server where a doctor can log in and perform remote diagnosis, such a framework is well suited for developing regions with poor patient to doctor ratios. Sana is available only on Android platform, so we also developed a Symbian-based client for Sana to make it more reachable as Symbian is the most popular mobile phone platform in India.

In our field deployment, we found that 58% of the surveyed population was identified to have high or moderate risk of CVD. Though these findings were in line with WHO warnings about spread of CVD in India, we find it very alarming as this study was done in a rural area where most of the population was much more involved in physical work than in an urban area. Detailed analysis of the collected data also demonstrated that the proposed approaches conflict with each other in CVD risk detection for Indian population. For a large number of cases (approximately 59%), different encoded approaches categorized the same person in a different CVD risk category. These results clearly indicate the need for comprehensive clinical data collection to come up with the right set of parameters that can accurately detect CVD risk for Indian population.

In our current study, due to limited resources and time constraints, each person was visited only once by the healthcare worker. However, we believe that several timely visits of the healthcare worker may be necessary (to look at time variation of the involved medical parameters) before categorizing a person to any CVD risk category. Although in the current system we are depending upon healthcare workers to collect data, the system can use ideas of participatory sensing to directly collect without an intermediary if deployed in an urban setting. Since *CVDMagic* can do processing on the phone itself to calculate the risk, it is possible to self-asses the risk by an urban resident who possesses a smart phone and can get readings for blood pressure and glucose levels from a laboratory.

In addition to patients and healthcare worker, doctors and IT administrators also interact with the *CVDMagic* system. Success of the whole end-to-end system depends on adaptability of each of the stakeholder. In our current post-deployment survey, both healthcare worker and IT administrator expressed complete satisfaction in handling *CVDMagic* . We plan to look into handling privacy and security issues that will arise from wide-spread deployment as well as sensitivity about certain health issues.

To conclude, we find that our proposed *CVDMagic* can be used to efficiently and accurately perform the comprehensive data collection. Its success in rural environments and ease of use, as proclaimed by healthcare worker and IT administrator, makes it a suitable platform for a developing country like India.

6. REFERENCES

[1] Who cvd-risk management package for low-and medium-resource settings. `http://whqlibdoc.who.int/publications/2002/9241545852.pdf`, Retrieved on March 21, 2011.

[2] V. Anantraman, T. Mikkelsen, R. Khilnani, V. Kumar, A. Pentland, and L. O. Machado. Open source handheld-based emr for paramedics working in rural areas. *AMIA Annual Symposium Proceedings*, 12-16, 2002.

[3] J. A. Blaya, T. Cohen, P. Rodriguez, d Jihoon Kim, e, and H. S. Fraser. Personal digital assistants to collect tuberculosis bacteriology data in peru reduce delays, errors, and workload, and are acceptable to users: cluster randomized controlled trial. *International Society for Infectious Diseases*, 13(3):410-18, 2008.

[4] B. DS, R. D, and T. JP. Taking it to the streets: recording medical outreach data on personal digital assistants. *Comput. inform. Nurs*, Sep-Oct;23(5):250-5, 2005.

[5] T. A. Gaziano, C. R. Young, G. Fitzmaurice, S. Atwood, and J. M. Gaziano. Laboratory-based versus non-laboratory-based method for assessment of cardiovascular disease risk: the nhanes i follow-up study cohort. *The Lancet*, 371, March 15, 2008.

[6] S. Goenka, D. Prabhakaran, V. S. Ajay, and K. S. Reddy. Preventing cardiovascular disease in india-translating evidence to action. *Current Science*, 97, No. 3, 10 August 2009.

[7] B. J and F. HS. Development, implementation and preliminary study of a pda-based tuberculosis result collection system. *AMIA Annu Symp Proc*, 41-5, 2006.

[8] Z. Jin, J. Oresko, S. Huang, , and A. C. Cheng. Hearttogo: A personalized medicine technology for cardiovascular disease prevention and detection. *Life Science Systems and Applications Workshop. IEEE/NIH*, 2009.

[9] R. Joshi, M. Cardona, S. Iyengar, A. Sukumar, C. R. Raju, K. R. Raju, K. Raju, K. S. Reddy, A. Lopez, and B. Neal. Chronic diseases now a leading cause of death in rural india mortality data from the andhra pradesh rural health initiative. *Journal of Epidemiology*, 2006.

[10] S. Kanjilal, V. Rao, M. Mukherjee, B. Natesha, K. Renuka, K. Sibi, S. Iyengar, and V. Kakkar. Application of cardiovascular disease risk prediction models and the relevance of novel biomarkers to risk stratification in asian indians. *Vascular Health and Risk Management*, 4,199-212(1), 2008.

[11] S. Lemieux, J. P. Despres, S. Moorjani, A. Nadeau, G. Theriault, D. Prudhomme, A. Tremblay, C. Bouchard, and P. J. Lupien. Are gender differences in cardiovascular disease risk factors explained by the level of visceral adipose tissue? *Diabetologia*, 37;757-64, 1994.

[12] V. Mohan, C. Shanthirani, M. Deepa, M. Datta, O. Williams, and R. Deepa. Community empowerment - a successful model for prevention of non-communicable diseases in india-the chennai urban population study (cups - 17). *JAPI*, 54, November 2006.

[13] Y. P, de Courten M, P. E, G. G, and Pryor. The development and evaluation of a pda-based method for public health surveillance data collection in developing countries. *Int. J. Med. Inform*, 78(8):532-542, 2009 Aug.

[14] D. Ramachandran, V. Goswami, and J. Canny. Research and reality: Using mobile messages to promote maternal health in rural india. *ICTD*, 2010.

[15] B. Shah and P. Mathur. Surveillance of cardiovascular disease risk factors in india: The need & scope. *Indian journal of Medical Research*, 132,634-642(5), 2010.

[16] B. Shah and P. Mathur. Surveillance of cardiovascular disease risk factors in india: the need and scope. *Indian J Med Res 132*, pp 634-642, November 2010.

[17] M. J. Vale, M. V. Jelinek, et al. Coaching patients on achieving cardiovascular health(coach):a multicenter randomized trial in patients with coronary heart disease. *Arch Intern Med*, 163, pp. 2775-2783, 2003.